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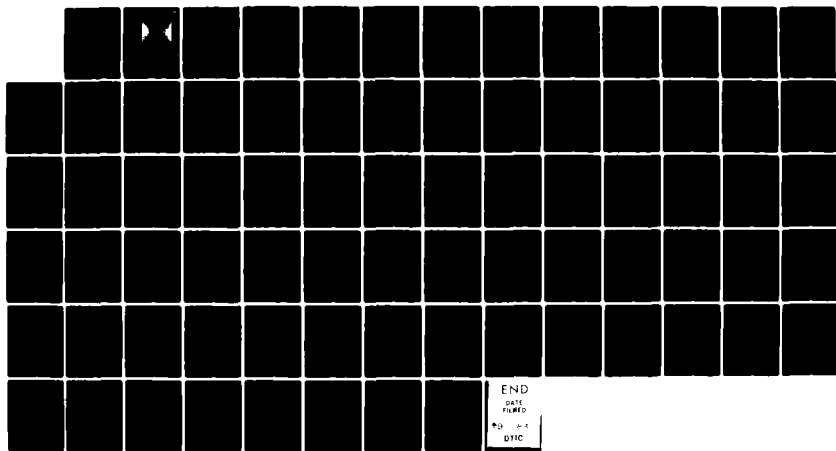
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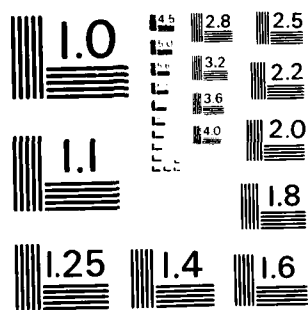
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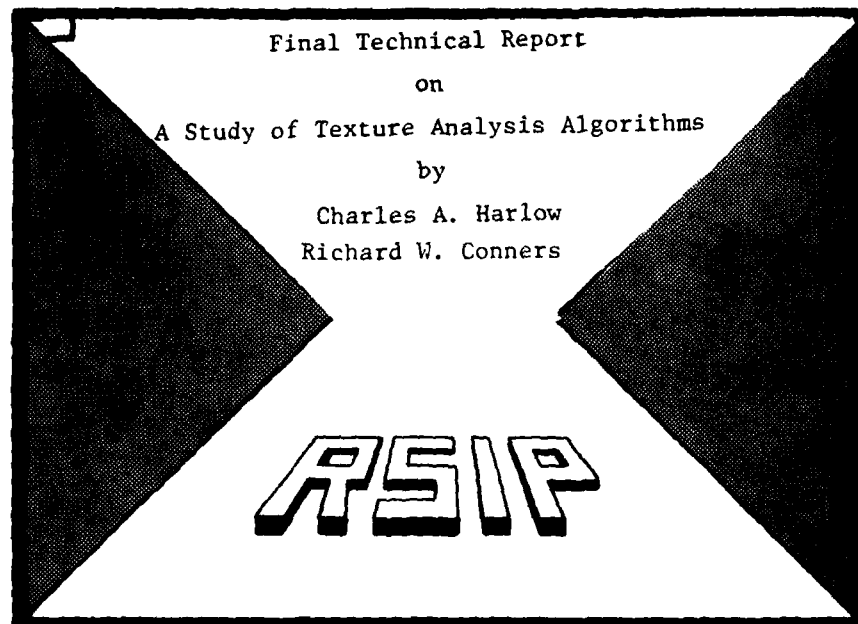


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Final Technical Report
on
A Study of Texture Analysis Algorithms
by
Charles A. Harlow
Richard W. Conners

February 1983

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The desire was to develop improved texture analysis methods through a systematic theoretical development process. The goal was to create a texture analysis algorithm which could match a level of human perception. The studies described include a comparison of some texture analysis algorithms, the development of a structural texture analyzer based on statistical methods, the examination of texture pairs which are counter examples to the Julesz conjecture, the development of an image segmentation method based on texture analysis methods, the development of a target recognition strategy based on texture methods, and finally a formal mathematical procedure for defining texture measures.

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ABSTRACT

This is the final report for the Air Force Office of Scientific Research grant entitled "A Study of Texture Analysis Algorithms." As such this report attempts to provide an overview of the research that was performed and to provide a chronology of the events which precipitated the various studies conducted. The research described ranges from developing a theoretical comparison method for evaluating the innate abilities of texture analysis algorithms to a formal mathematical method for defining texture measures. The desire was to develop improved texture analysis methods through a systematic theoretical development process. The goal was to create a texture analysis algorithm which could match a level of human perception. The studies described include a comparison of some texture analysis algorithms, the development of a structural texture analyzer based on statistical methods, the examination of texture pairs which are counter examples to the Julesz conjecture, the development of an image segmentation method based on texture analysis methods, the development of a target recognition strategy based on texture methods, and finally a formal mathematical procedure for defining texture measures.

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1. INTRODUCTION

Purpose of this report is to review the research sponsored by the Air Force Office of Scientific Research under the title "A Study of Texture Analysis Algorithms from March 1, 1979 to August 31, 1982. Further an attempt will be made to put the results obtained in context of what was happening in the image analysis community as a whole.

The major research questions considered were the following.

- (i) Which texture analysis algorithm is the best?
- (ii) Can this algorithm be improved?
- (iii) If so how can the improvement be made?
- (iv) Can it be improved to the point where it can match a level of human texture perception?
- (v) Can it be used to obtain visually meaningful information?
- (vi) How can the algorithm be used to perform useful image analysis tasks?

The answers obtained to these questions will be described in chronological order. In those instances where the results have been published in a journal the descriptions will be brief with only the context in which the research was performed given and a summary of the major findings presented. In those instances where the results have not yet appeared in a journal the description of the research and the results will be more complete.

Since most of the work has centered around the spatial gray level dependence method (SGLDM) texture algorithm [1,2,3] the discussion will begin with a brief description of this procedure.

2. A DESCRIPTION OF THE SGLDM

The heart of the SGLDM is the cooccurrence matrix. To define this matrix some definitions are in order.

Definition 1: A tile T is a closed topological disk.

Definition 2. A function $\sigma: E^2 \rightarrow E^2$ is called an *isometry* or *congruence transformation* if it maps the Euclidean plane onto itself and if the function preserves distance. That is, if \underline{x} and \underline{y} are points in E^2 then $||\underline{x} - \underline{y}|| = ||\sigma(\underline{x}) - \sigma(\underline{y})||$.

A cooccurrence matrix $S(\delta, T) = [s(i, j, \delta, T)]$ is a matrix of estimated second-order probabilities where each element $s(i, j, \delta, T)$ is the estimated probability of going from gray level i to gray level j given the displacement vector $\delta = (\Delta x, \Delta y)$ and T , the region size and shape used to estimate this probability. In this context T is a tile such that $s(i, j, \delta, T)$ is estimated from the restriction of the picture function $g(\underline{x})$ to $\sigma(T)$ where σ is a translation isometry. Computationally $S(\delta, T)$ is determined using the equation

$$s(i, j, \delta, T) = \frac{O\{\underline{x} | \underline{x}, \underline{x} + \delta \in \sigma(T), g(\underline{x}) = i, g(\underline{x} + \delta) = j\}}{N}$$

where $N = O\{\underline{x} | \underline{x}, \underline{x} + \delta \in T\}$ and where O denotes the order of the set, i.e., the number of elements.

In what follows it is frequently convenient to consider $\delta = (\Delta x, \Delta y)$ not in a cartesian form but rather in a polar form $\delta = (d, \theta)$ where $d = \max [\Delta x, \Delta y]$ and $\theta = \arctan (\Delta y / \Delta x)$. In this polar form d is called the intersample spacing distance and θ is called the angular orientation

Typically five measures have been defined off each cooccurrence matrix. These are

1. Energy

$$E(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} [s(i, j, \delta, T)]^2 \quad (1)$$

2. Entropy

$$H(\delta, T) = - \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} s(i, j, \delta, T) \log [s(i, j, \delta, T)] \quad (2)$$

3. Correlation

$$C(\delta, T) = \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i - \mu_x)(j - \mu_y) s(i, j, \delta, T)}{\sigma_x \sigma_y} \quad (3)$$

4. Local Homogeneity

$$L(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} \frac{1}{1 + (i-j)^2} s(i, j, \delta, T) \quad (4)$$

5. Inertia

$$I(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i-j)^2 s(i, j, \delta, T) \quad (5)$$

where

$$\mu_x = \sum_{i=0}^{L-1} i \sum_{j=0}^{L-1} s(i, j, \delta, T), \quad (6)$$

$$\mu_y = \sum_{j=0}^{L-1} j \sum_{i=0}^{L-1} s(i, j, \delta, T),$$

$$\sigma_x = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i - \mu_x)^2 s(i, j, \delta, T),$$

and

$$\sigma_y = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (j - \mu_y)^2 s(i, j, \delta, T).$$

and where L is the number of gray levels.

The cooccurrence matrices would seemingly be motivated by the early work of Julesz [4]. Darling and Joseph [1] first defined measures off these matrices for use in texture analysis and Haralick, et al [3,4] can be credited for using these matrices as the heart of a texture analysis system.

3. COMPARISON AND IMPROVEMENT OF TEXTURE ALGORITHMS

The motivation for a comparison of texture analysis algorithms is clear since the first choice an investigator faces when attempting to solve an applications problem is the selection of the algorithm to be used. Yet in 1979 there had been only one major effort to compare the relative merits of various texture algorithms. This study was conducted by Weszka, Dyer and Rosenfeld [5]. Admittedly other studies had involved the use of multiple texture analysis algorithms. Kruger, et.al [6] had employed both the SGLDM and the power spectral method (PSM) [7] but no real evaluation was done. Rather the use of multiple algorithms was merely coincidental to his work on the computer assessment of Coal Workers' Pneumoconiosis. Mitchell, et. al [8] did attempt to compare the max-min method to the SGLDM but the major thrust of the work was in introducing the Max-Min method with only a small effort expended to do the comparison.

The Weszka, Dyer and Rosenfeld study compared the relative abilities of the SGLDM, PSM, gray level run length method (GLRLM) [9] and the gray level difference method (GLDM) [5] to discriminate terrain types from aerial photographs. The metric of comparison was the percentage of overall correct classification, a classification result comparison (CRC).

The conclusions reached can be summarized as follows:

1. The features based on the SGLDM and the GLDM did about equally well in separating the various classes considered.
2. The features based on the SGLDM and the GLDM did somewhat better than the features based on the PSM.
3. The features based on the GLRLM performed markedly worse than the features based on the other three methods, so much so in fact, that the GLRLM was not considered in their main study.
4. The discriminatory power of the SGLDM and the GLDM improves when several intersample spacing distances are used.

The main drawback of the Weszka, Dyer and Rosenfeld work was the CRC methodology employed. This comparison approach has three significant drawbacks. These are:

1. To obtain a high confidence level in the results, the data base must be large.
2. The comparison results obtained from a data base of aerial photos may not be indicative of the relative power of the algorithms if they are applied to data bases of other textural types.
3. The CRC does not provide any insight into why one algorithm performs poorly and another performs well.

This last point means the CRC cannot be used, for example, to determine whether the set of features defined on the power spectra are inadequate thus causing its poor performance on a particular problem or whether the power spectra is itself at fault because it does not contain all the important texture information needed to do the discrimination. Rather the CRC measures the effectiveness of whole texture analysis systems such as is shown in Figure 1.

To address the obvious shortcomings of the CRC approach the authors developed a new theoretical evaluation procedure [10]. This methodology was not dependent on the set of features used with an algorithm but rather it measured the amount of important texture-context information contained in the intermediate matrices of the algorithm. The algorithms considered were the SGLDM, GLDM, GLRLM and PSM. These algorithms were chosen because they were frequently used and because considering them allowed a check of the results obtained using the new procedure with those obtained by Weszka, Dyer and Rosenfeld.

The principal results obtained by the new evaluation method were

- (i) The cooccurrence matrices contain more important texture context information than the intermediate matrices of any of the other algorithms;

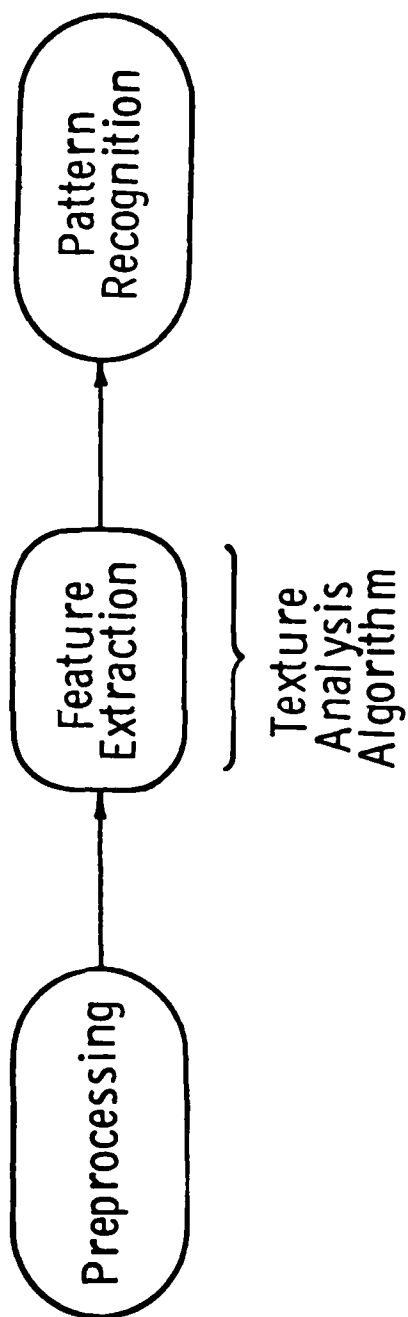


Figure 1. The basic steps involved in any texture analysis system. In performing texture analysis, the texture algorithm is the feature extraction step.

- (ii) the discriminatory power of the cooccurrence matrices increases as more δ 's are used;
- (iii) to infer visual qualities of patterns in general requires more than one δ value be used; and
- (iv) the energy entropy, correlation, local homogeneity and inertia measures defined in Equations 1-5 do not gauge all the important texture-context information contained in the cooccurrence matrices.

These conclusions are reinforced by the fact that in those areas where there was an overlap there was a very good agreement between the results obtained using the new theoretical method and those obtained by Weszka, Dyer and Rosenfeld.

The only difference between the Weszka, Dyer and Rosenfeld results and those obtained using the theoretical approach evolves around the fact that GLDM and the SGLDM did about equally well discriminating terrain types whereas the cooccurrence matrices were shown to contain more important texture-context information than the intermediate matrices of the GLDM. If the SGLDM is indeed innately more powerful than GLDM one might expect some noticeable difference in the performance of the two algorithms on real world data.

However, a very preliminary study shows at least one explanation for this difference. Consider the textures shown in Figure 2. These two textures can be discriminated based on information contained in the cooccurrence matrices. However, these two textures cannot be discriminated by the energy, entropy, correlation, local homogeneity and inertia measures (Equations 1-5). Consequently this leads one to believe that the comparable performance of the two algorithms on the terrain data might be due to the poor quality of energy, entropy, correlation, local homogeneity, and inertia measures and not to the fact

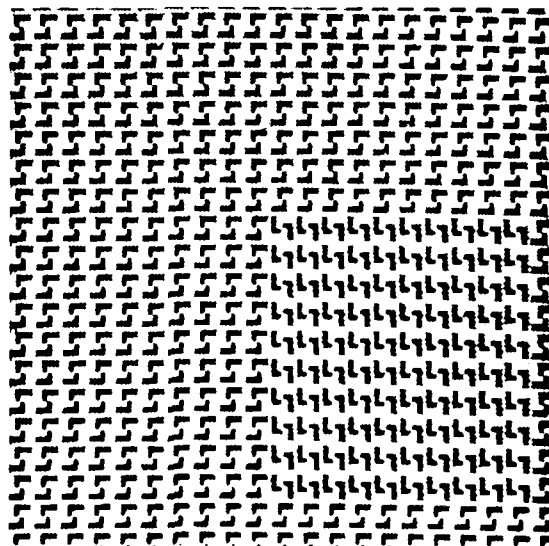


Figure 2. Two textures which cannot be discriminated by the energy, entropy, correlation, local homogeneity and inertia measures but which can be discriminated by information contained in the cooccurrence matrices.

that the cooccurrence matrices do not contain more texture-context information than the intermediate matrices of the GLDM.

The only other algorithm which has been shown to be comparable to the SGLDM is the max-min method [8]. As was stated previously Mitchell, et.al [8] compared the max-min procedure to the SGLDM using the CRC criteria. The comparison together with the fact that the max-min method is computationally less complex than the SGLDM would seemingly make it a desirable alternative.

However, there are three points to be considered. First it is unclear how many δ values were used in the application of the SGLDM. Consequently the full power of the SGLDM may not have been utilized. Secondly, the max-min method cannot discriminate the texture pair shown in Figure 2. Remember that these textures cannot be discriminated by the energy, entropy, correlation, local homogeneity, and inertia measures hence part of the reason for comparable performance could be the poor quality of the measures defined off the cooccurrence matrices. Lastly the max-min method cannot discriminate many very simple textures such as those shown in Figure 3. Note that the cooccurrence matrices contain information that can easily be used to discriminate these patterns. The inability of the max-min method to discriminate such truly simple patterns is in the authors' minds the most damaging evidence against it. This inability seemingly indicates an innate weakness in the algorithm.

The research work described in [10] and in formulating the above arguments addresses research questions (i) and (ii) given in the Introduction. In particular the answer to (i) appears to be that the SGLDM is the best available algorithm in that the cooccurrence matrices upon which it is based contain more important texture context information. Further the work indicates that the energy, entropy, local homogeneity,

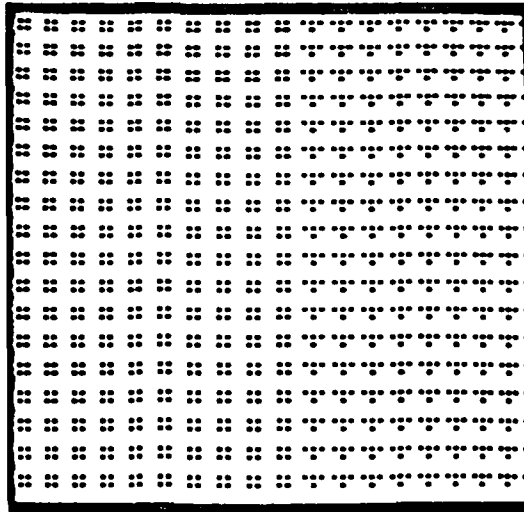


Figure 3. Very simple textures which cannot be discriminated by the max-min method. Note the cooccurrence matrices.

and inertia measures are weak. Consequently the most reasonable course of action seemed to be to attempt to define new more powerful measures which gauge all the important texture-context information contained in the cooccurrence matrices.

4. GAUGING VISUALLY PERCEIVABLE QUALITIES OF TEXTURE PATTERNS

Given the above, question (iii) in the Introduction becomes "how can superior texture measures be defined?" The problem of defining quality measures has plagued image analysts for years. The authors' desire was to develop as formal a measurement definition process as possible. And, at the very least, the hope was that some engineering type design principles could be found for formulating a set of new measures. Obviously as the research progressed the methods of approach varied. In this section some of the tactics used will be described. The most current thinking on the problem will be given in another section.

When the measurement definition work began it seemed to the authors that "best" measures would be ones which could be used to gauge visually perceivable qualities of patterns. Consequently the first engineering design requirement was that each new measure should be able to gauge a visual quality of a pattern.

Since at the time this research was being conducted there had only been one study, one done by Rosenfeld and Troy [11], indicating that a measure defined off cooccurrence matrix could be used to gauge a visual quality, there was some doubt as to whether any such measures could be defined. The Rosenfeld and Troy study was performed in 1970 and considered the use of the inertia measure to gauge textural coarseness. While the results of the study were positive only a few textures were considered. Further since no follow up studies were reported on this topic the ability to define a set of measures each of which, indeed any of which, satisfied the design requirement seemed in doubt.

Consequently the first task was to define a measure which could gauge some visual quality. After a review of some perceptual psychology

literature a candidate visual quality was found, the quality of texture periodicity. Psychologists [12,13] have believed for sometime that humans can effortlessly detect periodicity. The reason for choosing this particular perceptual quality was that periodicity has a precise mathematical definition. Perceptual concepts are in general vaguely defined without a concise mathematical translation.

Research considering periodic textures quickly yielded a number of results. To explain these results consider the texture shown in Figure 4. As will be observed it is made up of small black squares regularly spaced on a white background.

Consider, for a moment, only the $\theta = 0^\circ$ (horizontal) direction. It can be shown that for T large enough the following observations about the horizontal cooccurrence matrices $S(d, 0^\circ, T)$ (note it is assumed here that $\delta = (d, \theta)$), $d = 1, 2, \dots$, are true.

1. $S(\ell_H, 0^\circ, T)$ is a diagonal matrix, i.e., it has no nonzero off diagonal elements.
2. $S(d, 0^\circ, T)$, $d = 1, 2, \dots, \ell_H - 1$ have nonzero off diagonal elements.
3. $S(\ell_H + n, 0^\circ, T) = S(m\ell_H + n, 0^\circ, T)$, $m, n = 1, 2, \dots$, that is the horizontal cooccurrence matrices are periodic with period ℓ_H .

The comments concerning the texture of Figure 4 generalize to any periodic texture $g(\underline{x})$. If (ρ, θ) is a vector indicating the period of $g(\underline{x})$ in the direction θ then it can be easily shown that for T large enough

1. $S(\rho, \theta, T)$ is a diagonal matrix;
2. $S(d, \theta, T)$, $d = 1, 2, \dots, \rho - 1$, have nonzero off diagonal elements; and
3. $S(\rho + n, \theta, T) = S(m\rho + n, \theta, T)$, $m, n = 1, 2, \dots$, that is $S(d, \theta, T)$ is periodic with period ρ .

The above indicates that to detect periodicity one must detect the presence or absence of nonzero off diagonal elements in the cooccurrence matrices. Consequently a possible form for a measure which could gauge

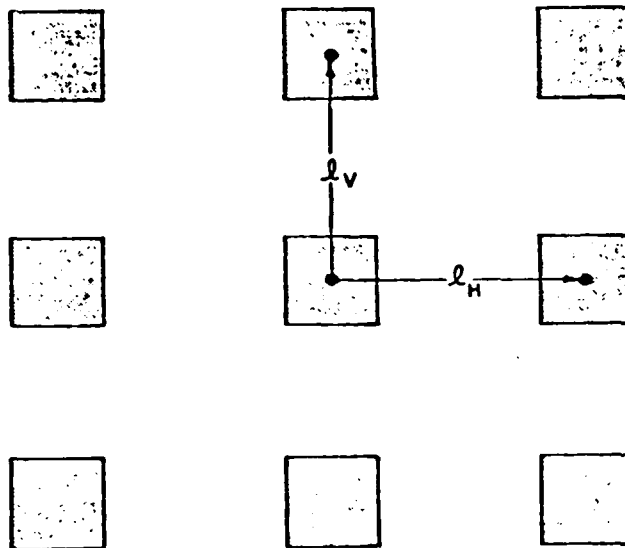


Figure 4. A simply periodic texture composed of squares which are regularly spaced on a white background.

periodicity is

$$\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} |i - j|^n S(d, \theta, T) \quad (7)$$

where n is a natural number. For any measure of this form an examination of the measurement's values as a function of intersample spacing distance can be used to detect periodicity of a pattern.

In particular, consider the inertia measure defined in Equation 5. Note that the inertia measure is of the form given in Equation 7. Hence the above observations tell us that this measure can be used for periodicity detection. To see how this can be done consider the plot shown in Figure 5. This plot is of the horizontal inertia measure computed from the texture of Figure 4. It is plotted as a function of the intersample spacing distance d . Two points should be noted about this plot. First, the points where the inertia measure is zero, i.e., take on minima, correspond to intersample spacing distance values which are integer multiples of ℓ_H . Secondly, note the periodic structure of the inertia measure. This reflects the periodic structure of the matrices $S(d, \theta, T)$, $d = 1, 2, \dots$.

Experiments with real world textures indicate that the inertia measure provides a basis for a "robust" method for determining periodicity. The idea is to look for local minima and periodic structure in the inertia plots just as in the example above.

Given that the inertia measure could be used for gauging periodicity the question was whether methods could be formulated to use this periodicity detection capability to find the unit pattern of a texture. Intuitively textures are defined by unit patterns and placement rules. If one could find the unit pattern and placement rules this certainly would be a step toward creating a structural texture analysis system.

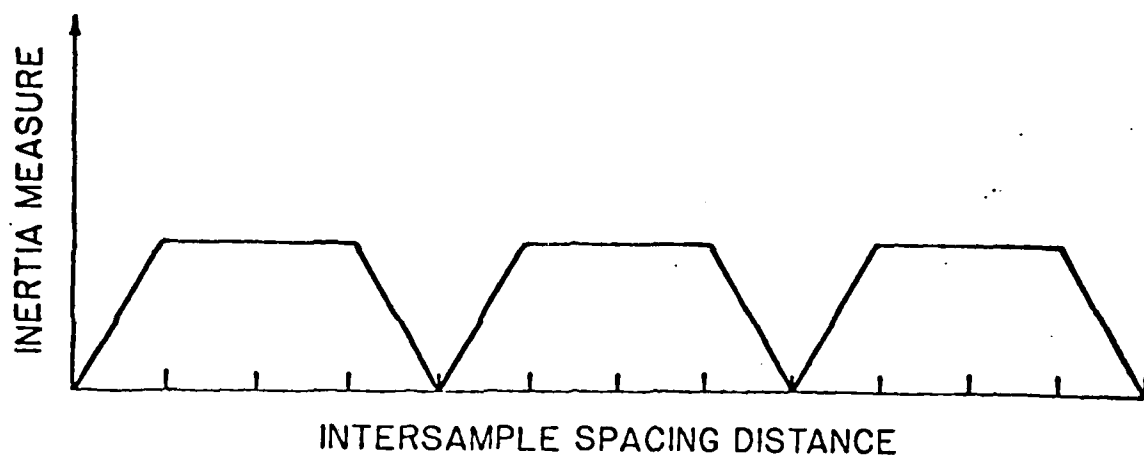


Figure 5. A plot of the horizontal inertia measure extracted from the texture given in Figure 4.

To attack this problem the authors formulated a model for texture based on mathematical tiling theory. The utility of this model was that it yielded the fact that every periodic texture could be decomposed into a period parallelogram unit pattern. The benefit gleamed by considering a period parallelogram unit pattern as the unit pattern of a periodic texture $g(\underline{x})$ stems from the fact that the shape, size and orientation of the unit pattern together with the rules governing its placement are all completely defined by two non-parallel vectors \underline{a} and \underline{b} . This fact is illustrated in Figure 6.

The above research results were reported in [14]. These results showed that a measure defined off the cooccurrence matrices could be used to gauge a visual quality of patterns. Secondly, it indicated that the measures defined off the cooccurrence matrices could be used as the basis for a structural textural analyzer, a structural analyzer based on statistical methods. This procedure is called a statistical structural analyzer (SSA).

To evolve the SSA required the definition of additional measures. Therefore work on the measurement definition problem continued. As the work progressed the concept of what embodies the "best" measurement set was refined. In particular the "best" measurement set is one which satisfies the following criteria.

1. Each measure in the measurement set should "gauge" some visually perceivable quality of a texture pattern.
2. The measures in the measurement set should be "independent."
3. Given any visually distinct pair of textures there should be at least one measure in the measurement set such that the value of this measure is different for the two textures comprising the pair.

In the above the meaning of the word "independent" can best be described by an example. Suppose that one has a measurement set composed of three measures, M_1 , M_2 , and M_3 . These measures are said to be independent if:

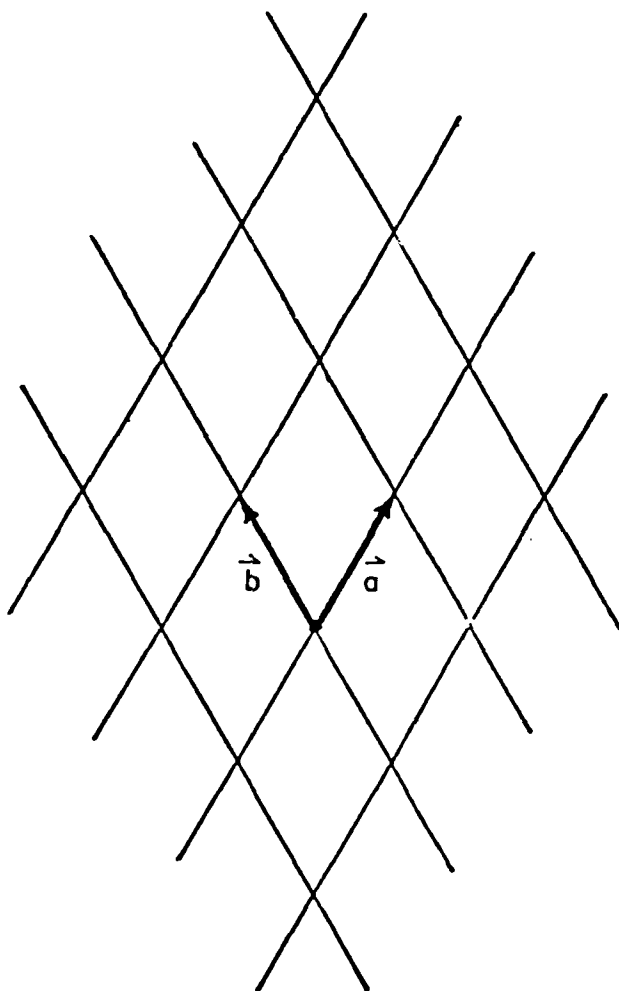


Figure 6. Two vectors \vec{a} and \vec{b} completely define the tile P and the placement rules of a period parallelogram unit pattern.

- a) there exists a visually distinct texture pair such that the expected values of the measures M_1 and M_2 are the same for both textures in the pair but the expected value of M_1 is different for the two textures;
- b) there exists another visually distinct texture pair such that the values of M_1 and M_3 are the same for both these textures but the expected value of M_2 is different; and
- c) there exists a third texture pair such that the expected values of the measures M_1 and M_2 are the same for both these textures but the expected value of measure M_3 is different for these two textures.

The extension of the above example to n measures is straightforward.

The above criteria, in essence, dictate the method for defining new measures. The required steps are:

- DS1. demonstrate the need for an additional measure in the measurement set;
- DS2. abstract the visual quality to be gauged and define a candidate measure to gauge this quality;
- DS3. establish that the candidate measure does gauge this quality; and
- DS4. verify that the candidate measure is independent of the previously defined measures.

To see how these design steps can be used consider the situation at this point in the measurement definition process. A measure, the inertia measure, has been defined. It has been shown that this measure can be used to gauge a visual quality of texture patterns, namely texture periodicity. Now the question is whether or not any other measure is needed, i.e., the question posed by DS1. To demonstrate a need for a new measure it must be shown that there exists at least one visually distinct texture pair which cannot be discriminated using the inertia measure. Such a texture pair is shown in Figure 7. This texture pair cannot be discriminated by the inertia measure but can be discriminated using information in the cooccurrence matrices not gauged by the inertia measure.

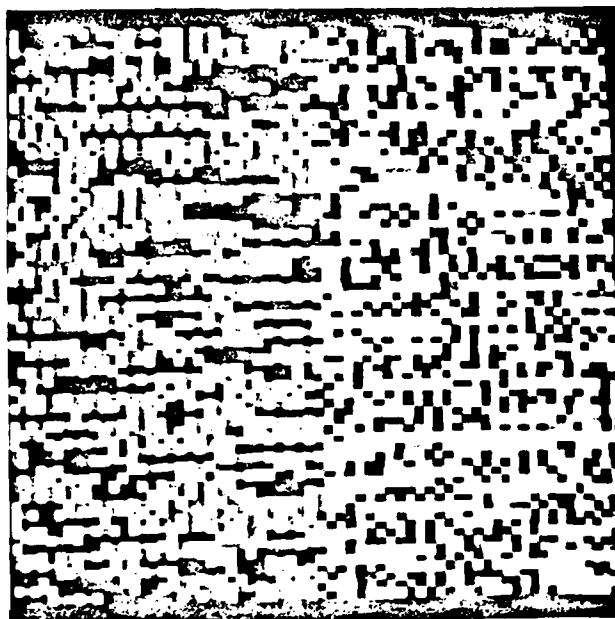


Figure 7. A visually distinct pair of textures which cannot be discriminated using the inertia measure but which can be discriminating by other information inside the cooccurrence matrices not gauged by the inertia measure.

In the case of this particular texture pair the human visual discrimination was attributed by Julesz [4] to the perceptual concepts of uniformity and proximity [15] or what Julesz called cluster formation. Consequently, the candidate visual quality required by DS2 was easily selected, the goal being to define a measure which gauged the perceptual concepts of uniformity and proximity. To determine what form the new measure should take an analysis of the expected values of the cooccurrence matrices of the two textures of Figure 7 was conducted. This led to the definition of a candidate measure. This candidate was tested on a number of other simple patterns whose human discrimination seemed at least partially based on uniformity and proximity.

Therefore this candidate was added to the measurement set. The new measure is called the cluster shade measure. It is defined by

$$A(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i + j - \mu_x - \mu_y)^3 s(i, j, \delta, T) \quad (8)$$

where μ_x and μ_y defined in Equation 6.

Using a similar design process another measure, the cluster prominence, was defined. The texture pair which demonstrated the need for the cluster prominence measure is shown in Figure 8. The cluster prominence is defined by

$$B(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i + j - \mu_x - \mu_y)^4 s(i, j, \delta, T) \quad (9)$$

where μ_x and μ_y the same as in Equation 6.

The studies resulting in the definition of the cluster shade and cluster prominence measures was reported in [16].

Before continuing three observations are in order. First, the cluster shade measure is "independent" of the five measures defined in

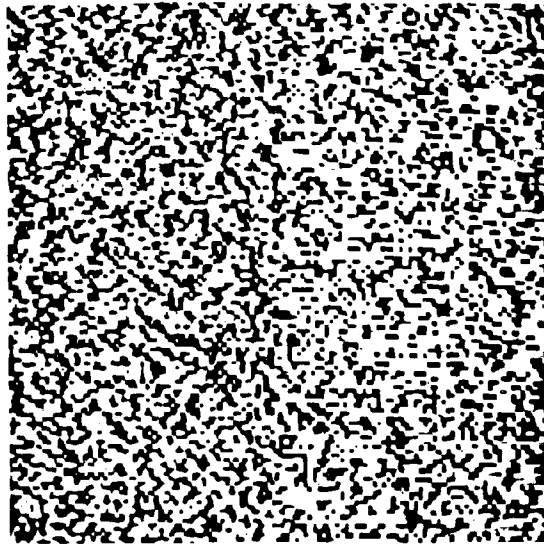


Figure 8. Two visually distinct texture pair which cannot be discriminated by the inertia or cluster shade measures. The existence of such a texture implies the need for another measure.

Equations 1-5. To see this observe that this measure can be used to discriminate the texture pair in Figure 2. Next the measurement set containing the inertia measure, the cluster shade measure and the cluster prominence measure is known not to be "complete" in that there is at least one visually distinct texture pair which cannot be discriminated by these three measures. Finally as unlikely as it might seem based on the Equations 4 and 9 which define the local homogeneity and the cluster prominence measures these two measures are seemingly highly correlated. Current research indicates that the local homogeneity measure may be the better choice for inclusion into the measurement set. However, the measurement set consisting of the inertia, cluster shade and local homogeneity is not complete either.

The new measurement definition process, i.e., the one based on design steps DS1-DS4, while being better than a purely heuristic approach still has a number of obvious shortcomings. First while the need for each measure is established (a requirement not usually imposed in purely heuristic approaches) the definition process is still performed by the human being examining cooccurrence matrices and abstracting a mathematical function to gauge some desired structure in these matrices. The difficulty here is that the number of textures whose cooccurrence matrices can be examined is usually very limited. Secondly, the human ability to abstract a mathematical function to gauge the structure is limited. There is no way to assure a minimal amount of correlation among the measures defined by the process. And, of course, finally there is the theoretically displeasing possibility that two investigators using this procedure could arrive at two completely different measurement sets. With all these facts in mind the problem continued to be investigated but the major emphasis of the research changed..

5. MATCHING A LEVEL OF HUMAN PERCEPTION

As will be remembered the 1962 Julesz study [4] had indicated that the second-order probabilities measured by the cooccurrence matrices could match at least the primitive level of human texture perception. This result is called the Julesz conjecture. It states that a necessary condition for two textures to be visually discriminable is that they have different second-order probabilities. Further the theoretical comparison study conducted by the authors had shown that cooccurrence matrices contain more important "texture-context" information than the intermediate matrices of any of the other texture algorithms tested.

Consequently, they seemed the obvious place from which to begin the development of improved texture analysis methods. However at about the time the measurement definition work was being conducted there were a number of papers presenting counter examples to the Julesz conjecture [17-22]. While some of the early patterns were, at best, barely discriminable and hence unconvincing, the later counter examples were quite distinct. One such convincing counter example is given in Figure 9.

Given the quality of the later counter examples it seemed appropriate to consider these textures in some detail since they seemingly challenged the adequacy of the cooccurrence matrices to match a level of human perception. For example Caelli and Julesz [18-20] had speculated that second-order probabilities were not adequate unto themselves but rather that other "detectors" were also required. In the experiments they conducted a total of four detectors were supposedly found which were required to augment the second-order probabilities. These so called Class B detectors included a "quasi-collinearity detector", a "corner

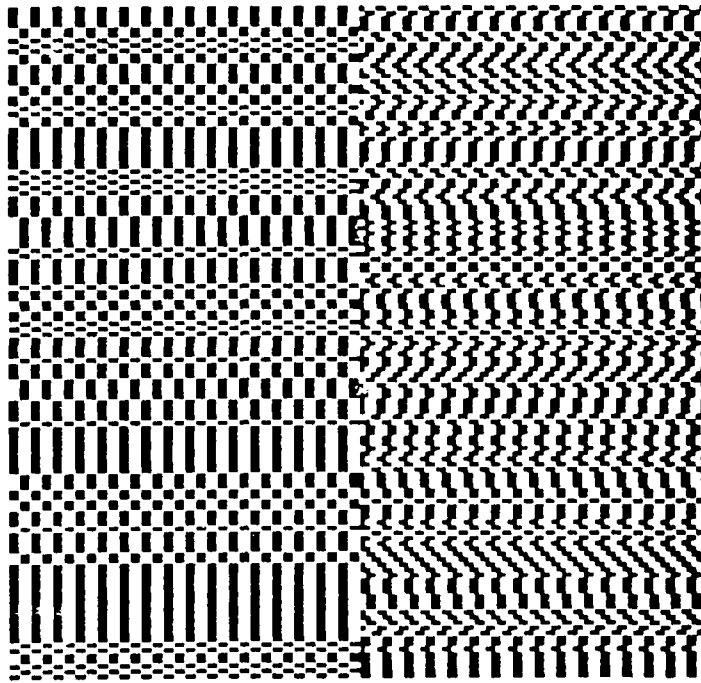


Figure 9. Two visually distinct textures which have identical second-order probabilities.

detector", a "closure detector", and a "granularity detector."

If the cooccurrence matrices could not be used to match a level of human perception then the best alternative for developing improved texture analysis procedures might be to attempt to create a totally new methodology. Consequently, a study was begun to consider the known counter examples. After this study started Gagalowicz [21,22] announced a revised form of the Julesz conjecture. This revision stated that a necessary condition for two textures to be discriminable is that they have different "local" second-order probabilities, i.e., second-order probabilities computed over a small region of the image. The previous form of the conjecture had involved "global" statistics, i.e., computed over a very large area. The results reported by Gagalowicz coincided with those that had thus far been obtained in the authors' study, hence they tended to reinforce one another. Therefore the most obvious conclusion was that the second-order probabilities gauged by the cooccurrence matrices were capable of matching a level of human perception. The only difficulty being the determination region size that should be used to estimate the appropriate local probabilities.

Consequently the research focused on finding ways to estimate the size region which should be used to insure that the resulting "locally" computed second-order probabilities would allow the discrimination of these textures. In many respects this work paralleled that which yielded a method for determining the unit pattern of periodic textures. The basic idea was the same and that was to see if "globally" computed cooccurrence matrices contained information on the size of area which should be used to do a "local" analysis. In the case of periodic textures the global analysis yields the unit pattern size and shape. In this instance regions having the same size and shape as the unit pattern seem the most

appropriate for a local analysis. The question to be addressed is whether a global analysis of these very special texture pairs would yield the most appropriate size over which a local analysis should proceed.

Actually an attraction for applying this global/local analysis process to the known counter examples was that it offered a unusual opportunity. The global analysis of most naturally occurring textures is usually all that is required to allow their discrimination. This follows from the fact that most natural occurring textures have different second-order probabilities. On the other hand a global analysis of the counter examples will not allow discrimination. Rather a local analysis must be performed. Consequently the thought was that the study of these textures might result in some useful information on the global/local analysis process itself.

For purposes of this discussion one can divide the known counter examples to the Julesz conjecture into two groups. One group is composed of structured textures. An example from this group is shown in Figure 10. A texture from this group is made up of the regular placement and random rotation of some elementary pattern. A visual analysis of such textures allows the determination of a region size which when regularly placed will always contain the rotated version of the elementary pattern from which the texture was generated. One of the nice characteristics of these textures is that one knows exactly what the output of the global analysis should be. In the case of the two textures shown the output should be a specification for a square region of whose sides correspond to the regular spacing of the rotated elementary patterns.

The other group is called the random patterns. An example of a texture pair from this group is shown in Figure 9. Note the size region which should be used to do the local analysis of these patterns is not so

obvious. Indeed it is not clear what the region size should be at all. Hence it is not clear what the output of the global analysis process should be.

First, consider the structured group of counter examples. Because each texture in this group is generated by regularly placing and then randomly rotating an elementary pattern [23] it can be argued that globally computed cooccurrence matrices contain information which will allow the determination of the regular placement rules used to generate the texture. The method for making this determination proceeds in a matter analogous to the determination of the period parallelogram unit pattern of periodic textures. Experiments were conducted on a number of such textures and it was found that such was the case. The result being precisely what one would want. Further it is of interest to note that once the region size was established over which the local analysis should proceed, it was possible to perfectly discriminate the counter examples considered based on the values of the cooccurrence matrices computed from the local region size selected.

The random group on the other hand contains a number of texture pairs which for each pair and any d and θ , the values of the second-order probabilities are equal to a constant, the same constant for all d and θ . In such cases it would appear that a global analysis contains no information about the scale of region that should be used in the local analysis. Consequently the research concentrated on these texture pairs.

The method of procedure was to consider for each texture pair this classification accuracies obtainable using various region sizes. The objective was to determine whether there was a "best" size region over which the local analysis should proceed. For a given texture pair and for each region size considered a theoretical lowest rate of misclassifica-

tion was computed. the theoretical lowest rate was based on the analysis of every possible pattern which could appear in a square region whose side is n pixels long. Each possible pattern was converted into a measurement vector of length n^2 where each element of the measurement vector was the gray level value of a point in the region. Considering every possible pattern allowed the distribution of the measurement vectors to be determined. Then a Bayesian decision procedure was employed to yield the minimum possible error rate.

Similarly for each region size considered cooccurrence matrices were extracted from every possible pattern for both textures and a probability distribution of the cooccurrence matrices was obtained for each texture. Based on these distributions a minimum error rate was calculated.

Figure 11 shows a typical set of results obtained. For this particular texture pair the theoretical rate of misclassification goes down quite rapidly as the region size increases. Further as the region size increases more δ values can be used to calculate cooccurrence matrices. This figure shows that as more of these δ values are used the error rate obtainable using the cooccurrence matrices also decreases.

A natural interpretation of the data shown in the figure is that the larger the region size used the better the classification accuracies obtainable albeit the fact that more and more δ values may have to be used to get the improved accuracy. Given this realization the natural way to interpret the global analysis results is that $s(i,j,\delta) = c$ for all i,j and δ implies that a large region should be used in performing local analysis.

Under this interpretation the evidence indicates that a global analysis always contains information about the scale at which a local analysis should proceed. If this result can be further verified, a substantial improvement in image segmentation methods could result.

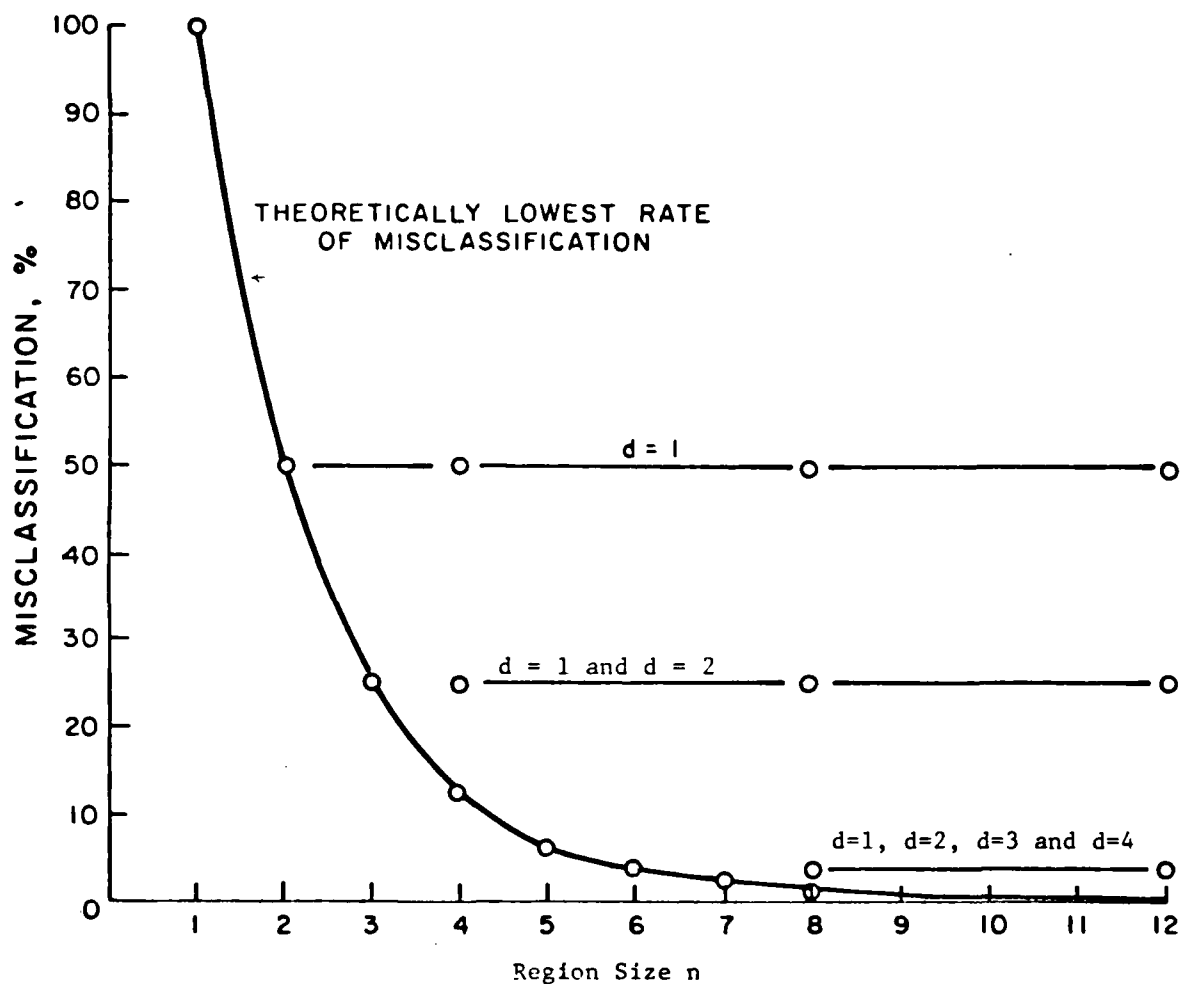


Figure 11. The theoretical versus actual rate of misclassification. The classification rates are shown as a function of region size. As can be seen when only one d value is used in computing cooccurrence matrices, namely $d = 1$, an error rate of 50% is obtained for all region sites n . When two values are used, namely, $d = 1$ and $d = 2$, an error rate of 25% is obtained. Again this misclassification rate seems independent of n . Finally notice that when three values of d , namely, $d = 1$, $d = 2$, $d = 3$ and $d = 4$ are used, a misclassification rate of 3.61% is obtained.

6. IMAGE SEGMENTATION AND TARGET DETECTION USING TEXTURE OPERATORS

Given that the cooccurrence matrices can be used to match a level of human performance the next problem it seemed appropriate to investigate was how measures defined off these matrices could be used to perform image analysis tasks. Since the authors have long felt that texture analysis methods could be used in image segmentation, the research effort turned to developing methods for employing measures defined off the cooccurrence matrices to segment scenes. The procedure developed is reported in [24]. Also described in [24] are the results obtained in using the procedure to segment a complicated high resolution urban scene. Consequently in this section only a general description of the procedure will be presented together with some motivation for the strategy employed.

Classically segmentation methods have been based on detecting edges or gauging uniformity by examining the histogram of the gray levels [25]. The cooccurrence matrices are known to contain both edge information as well as the first-order probabilities of the gray levels. Hence primitive operators based on these matrices would seem the logical generalizations of what has been used in the past. Consequently they offer the possibility of substantially improved the segmentation methods.

Texture is a property of a region. A texture pattern is composed of unit patterns and placement rules [14]. Viewed in this light the segmentation problem becomes one of analyzing macro- and micro-textures where the macro-texture is the interplay among the unit patterns and the placement rules and where the micro-texture is the pattern of the individual unit patterns which may themselves be textured. The idea was to employ

the same basic operators to each problem. If this could be accomplished a uniform data structure and analysis procedure could be used. Such uniformity should provide a better structured segmentation procedure.

There are basically two approaches to image segmentation. These are boundary detection and region formation [26,27,28,29]. Of these, region formation approaches are best suited for use with texture operators since these operators, inherently, characterize the qualities of a region. Region formation approaches can utilize either split, merge, or split and merge techniques. A merge procedure is a bottom-up approach where small regions are combined based on their perceived uniformity. Unfortunately, the statistical characterization of small regions is less reliable than for larger ones. Further in complicated scenes, such as urban scenes, small regions could belong to anyone of a large number of primitive classes such as grass, concrete, car, tree, etc. Combining these primitives to form a more meaningful grouping, i.e., commercial area, residential area, etc., would require a substantial reliance on semantic information. Providing such information is a difficult task.

A top-down procedure, such as a split procedure, seems to be best suited for use with texture operators since classification accuracies obtainable using texture analysis methods usually decrease as a function of region size. Therefore it is appropriate to use as large a region as possible and divide it as necessary. Further for an early vision system, a split procedure seems most appropriate since it begins with a few broad classes, i.e., commercial area, residential area, instead of a building, street or tree. Because of the nature of the texture algorithm as these large regions are split the texture measures computed from the smaller areas become more sensitive to finer detail. Consequently, classes

whose differentiation depends on finer detail can be handled later at some higher level using smaller region size and perhaps contextual information.

The proposed segmentation procedure is illustrated in Figure 12. In this procedure the scene is initially divided into a number of disjoint R_1 square regions such that the edges of these regions form a grid over the image. The size of the R_1 regions is some predetermined fixed value. Next a predetermined subset of the texture measures is computed from each of the R_1 regions. Given the values of the texture measures computed from a particular R_1 region, a decision is made as to whether this region contains only one of a predetermined set of K_1 classes. These K_1 classes are the ones the segmentation procedure has been taught to recognize at level 1 of the process. If it is decided that the region is so composed, then the region is labeled with the appropriate class label. If the region is determined not to contain just one of the K_1 classes then it is not assigned a class label. After all the R_1 regions have been analyzed, level 2 processing begins. The R_2 regions are formed by dividing the R_1 regions which were not assigned a class label. The division of each forms a number of disjoint square regions the edges of which would form a grid over the R_1 region being split. The size of the R_2 regions is some predetermined fixed value. Next a predetermined subset of the texture measures is computed from each of the R_2 regions. This subset could be entirely different than that used on level 1. Given the values of these texture measures computed from a particular R_2 region a decision is made as to whether this region contains only one of a predetermined set of K_2 classes. Note these K_2 classes can be different from the ones considered on level 1. Based on this determination a decision is

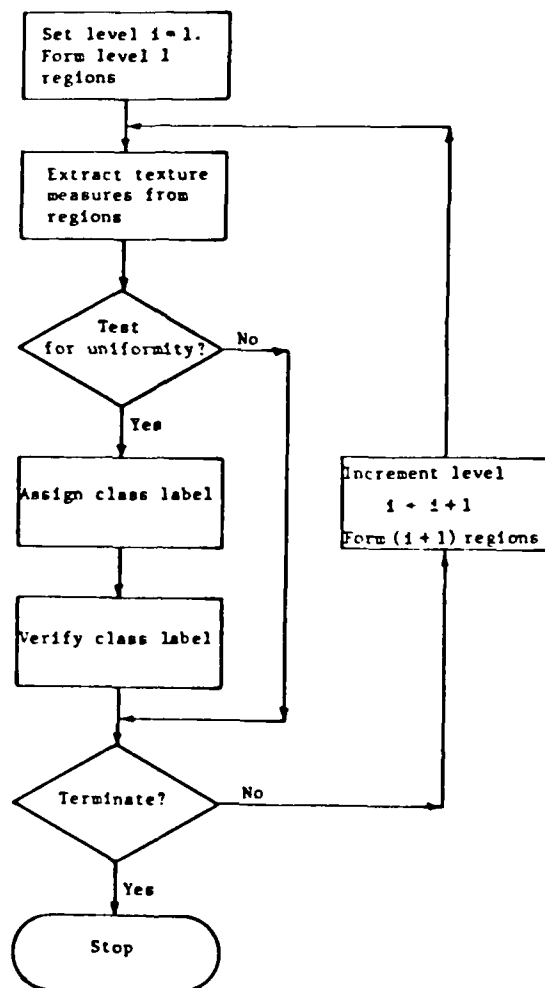


Figure 12. A flowchart of the basic steps involved in the proposed segmentation procedure.

made as to which class the region belongs or whether a further split is required. This iterative procedure continues until some predetermined level, say level l , is reached at which time all of the R_l regions are classified into K_l classes. A pyramid structure of this process is shown in Figure 13.

Region growing methods necessarily utilize clustering techniques [25,30,31,32]. Typically each subregion of the scene is characterized by a measurement vector $\underline{x} = [x_1, x_2, \dots, x_n]^t$, where x_i denotes the value of measurement i . Each such vector is a point in n -dimensional space E^n . Intuitively, measurement vectors computed from visually similar regions should lie "close" together in E^n while measurement vectors computed from visually dissimilar regions should lie "farther" apart. Consequently, measurement vectors computed from regions containing the same class should form a cluster in E^n .

There are two types of clustering algorithms, supervised and unsupervised. An unsupervised procedure is given no knowledge about the scene. The algorithm must find the number and extent of natural clusters in the measurement vector data obtained from the scene. Unsupervised procedures are usually more computationally complex and usually less accurate than supervised procedures [32]. They appear to require measurement vectors composed of uniformly high quality non-redundant measures, a requirement difficult to meet on all but the simplest image analysis problems.

Supervised approaches can utilize rudimentary a priori knowledge of the scene. Further they allow measurement selection to be performed so that only the "best" measures in the measurement vector need be used in making decisions. Supervised procedures force a predetermined structure where every region must be classified as one of K preassigned classes. Any region

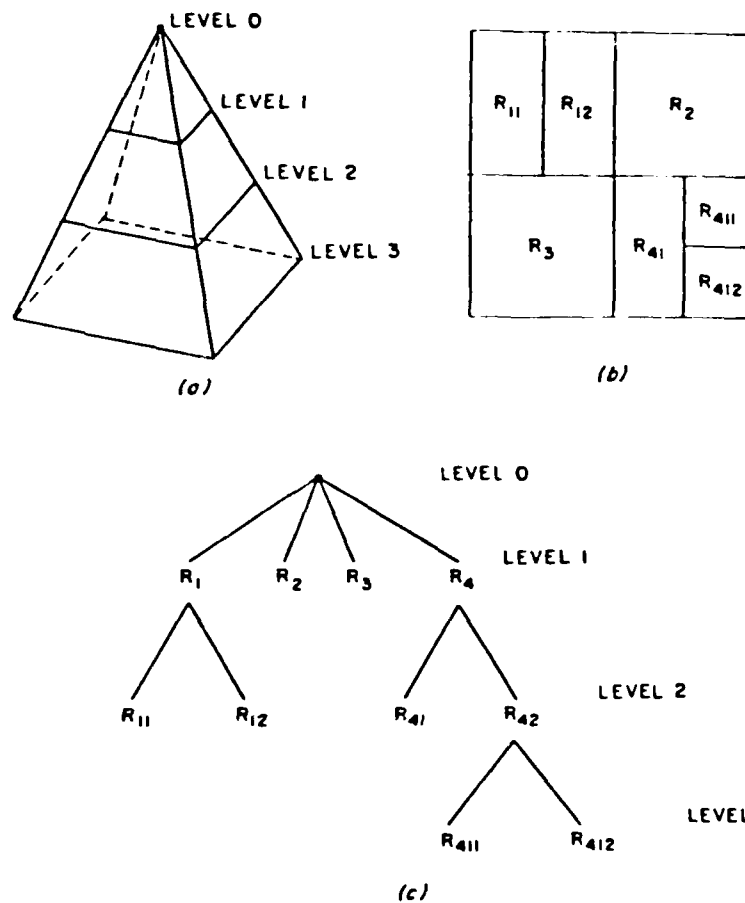


Figure 13. The natural pyramid structure of the segmentation. (a) An example of a three level segmentation where level 0 corresponds to the whole image, level 1 the first level of the segmentation, etc. (b) The regions formed during the segmentation. (c) A tree showing how the regions of (b) were formed.

not properly belonging to any one of these K classes will be incorrectly labeled, a most unfortunate property.

The proposed statistical segmentation procedure attempts to incorporate the useful attributes of both supervised and unsupervised approaches. It utilizes some knowledge of the scene by allowing one to select the classes to be considered at each level of processing. This is accomplished by selecting a training set for each class at each level where it is to be considered. Thus measurement selection can be performed so that only the best measures need be used in doing the segmentation. The statistical procedure provides the flexibility to determine whether a region is composed of all or a part of a class different from the K preselected classes it has been taught to recognize. The capability to detect such "unspecified" regions is an important part of the segmentation process [24]. The statistical procedure also provides a mechanism for identifying regions composed of two or more of the K preselected classes. These capabilities enable it to split such regions and to examine the resulting smaller regions using different classes and different level of detail.

The "clustering" method used is parametric in nature. Parametric methods have the advantage over nonparametric procedures in that they typically require fewer training samples. However this saving is obtained at the expense of demanding that class populations be defined by the parameters estimated. For this segmentation method, however, this requirement may not pose a severe limitation since classes whose population densities vary markedly from that assumed should have most of their as "unspecified" by the algorithm.

As was stated previously this procedure was applied to a high resolution urban scene to test its capabilities. The test involved the use

of nine level 1 classes. These were residential, commercial, mobile home, vehicle parking, water, dry land, multilane highway, runway and aircraft parking. In effect a one level segmentation was performed. While admittedly this test does not represent a complete evaluation of this segmentation procedure the results seem encouraging. The work to date all show that more research should be done both in evaluating the techniques and in optimizing the methodologies used in the procedure.

One interesting sidelight of the segmentation study was that the image used allowed a test of whether texture measures defined off cooccurrence matrices could gauge structure in complicated scenes. While a number of examples of structural information gauged by texture measures are given in [24] only one example will be presented here. This example involves a vehicle parking area. Figure 14 shows the basic structure of this area and gives the number of pixels between the various elements of the scene. Figure 15 shows plots of the local homogeneity, energy and entropy measures. The interesting point about Figure 15 is that it indicates that these measures can be used to determine the distances between the rows of the parking lot. Figure 16 shows the plot of the inertia measure computed along the same direction as the local homogeneity, energy and entropy measures of Figure 15. Note that no periodic structure can be detected in the inertia measure plot. Hence this measure cannot be used to detect this structure. Further it is interesting to note that the power spectrum cannot be used to detect this structure either since the power spectrum and inertia measure are essentially equivalent.

Target or object detection can be viewed as a special kind of image segmentation task; a task very important in scene analysis. In this situation

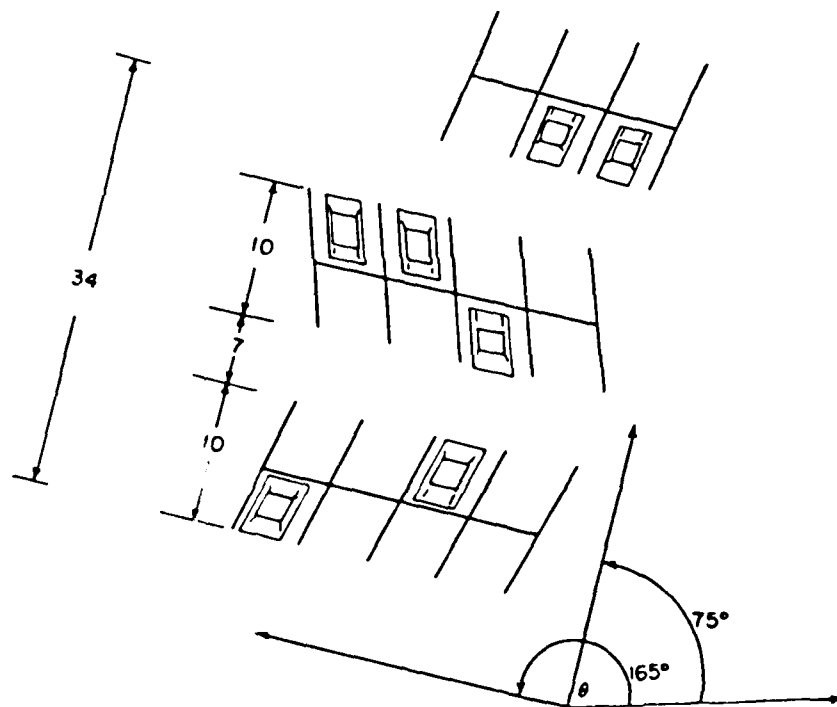


Figure 14. The structure of vehicle parking area. Also given is the number of pixels between elements of the scene.

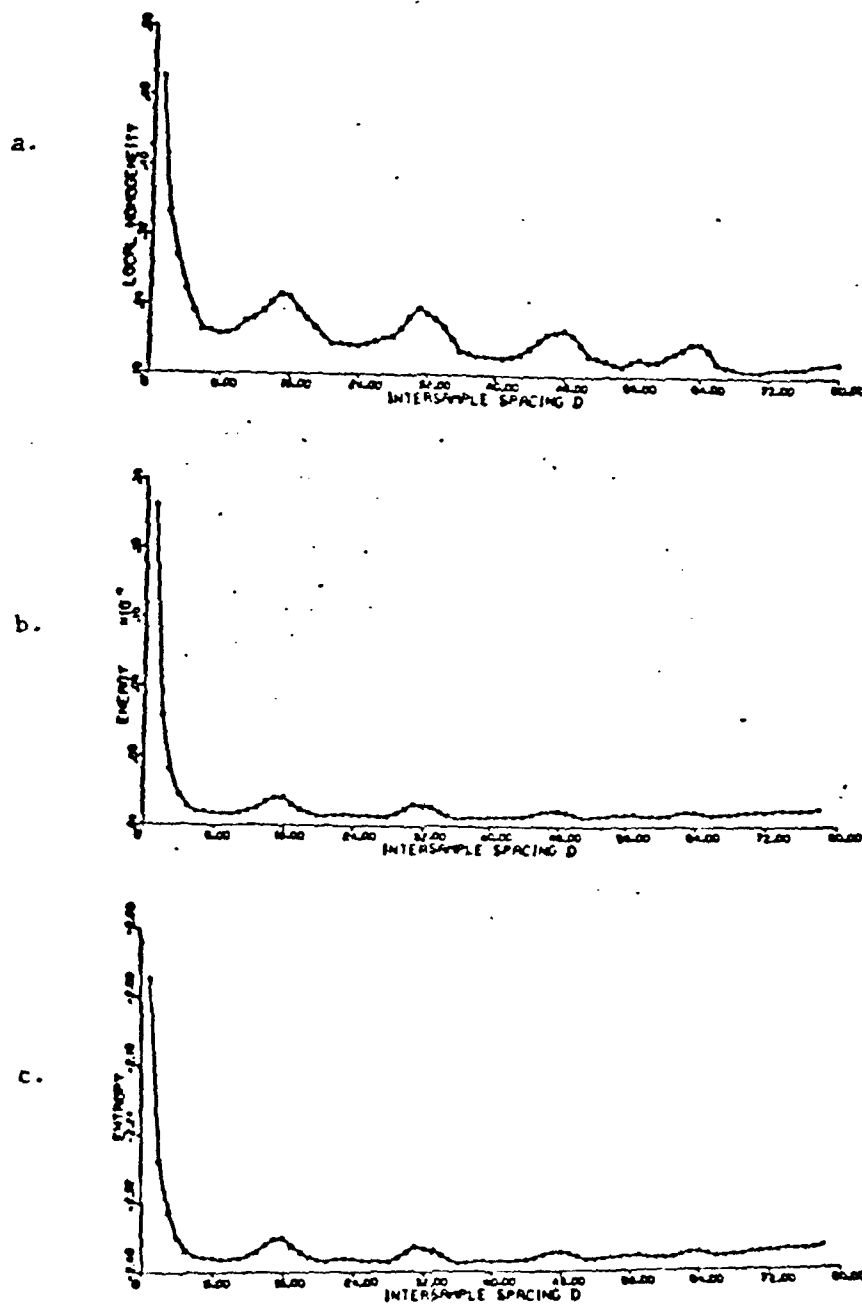


Figure 15. Plots of (a) local homogeneity, (b) energy and (c) entropy measures computed from the vehicle parking area along the $\theta = 75^\circ$ direction.

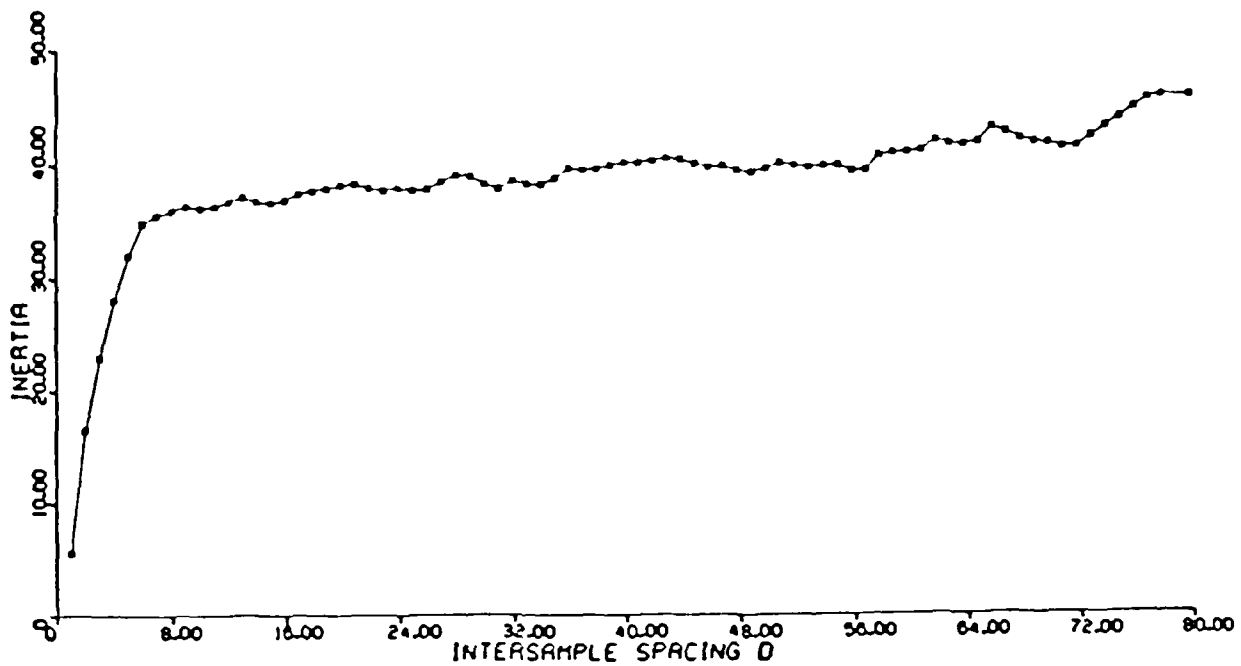


Figure 16. Plot of inertia measure computed from the vehicle parking area along the $\theta = 75^\circ$ direction.

the scene has to be segmented into regions containing targets and those without targets. While such a formulation limits the number of classes to be considered to only two, target and background, it requires a robust set of measurements to accomplish target detection in a variety of backgrounds. Ideally, one would like to utilize measurements which characterize only the targets and are invariant to the backgrounds in the scene. In actuality, one is forced to find a target characterization which is minimally sensitive to the background.

In a sense the target detection problem represents a logical continuation of the segmentation study reported above. Consequently, it seemed appropriate to test whether texture measures could be used to perform this task. While using texture measures to attack a target recognition problem might seem inappropriate it is important to point out that it can be shown that the texture measures defined using the co-occurrence matrices are sensitive to shape. Hence their use is not at all unreasonable.

To attack the target recognition problem special recognition software was developed. The scheme used is based on the fact that a target may appear against a number of possible backgrounds. What is desired is a set of measures which are sensitive to the presence of a target but insensitive to the background upon which it appears. Stated another way one wants a set of measures which if a target is present \underline{x} is a member of the distribution defined by the class condition density function $p(\underline{x}|T)$. If a target is not present then \underline{x} should not be a member of this distribution.

In our formulation we assumed $p(\underline{x}|T)$ was normal with mean vector $\underline{\mu}$ and covariance matrix Σ . Hence to determine whether \underline{x} is a member

of the distribution defined of $p(\underline{x}|T)$ only requires a Chi-square test similar that described in reference 24.

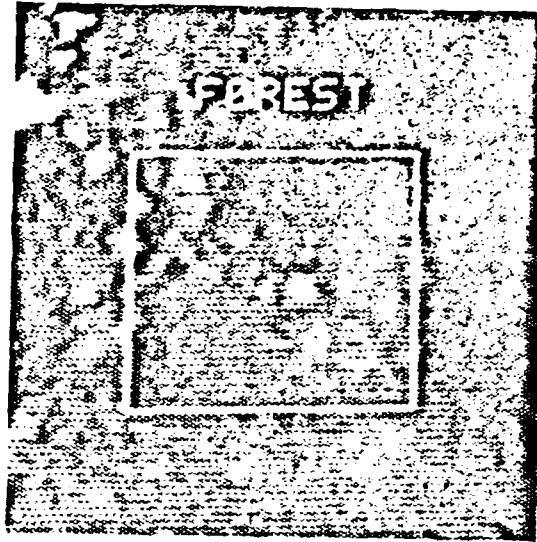
The only problem that remained was selecting the subset of the texture measures which is most sensitive to the target and least sensitive to the background. This was accomplished by writing a special measurement selection program. This forward sequential search procedure selects not only the subset of measures which should be used but also provides the value of $X_{d;\alpha}^2$ and hence the value of \underline{x} which gives the best classification accuracies.

The training data for the measurement selection program consists of measurements computed from regions containing only background and regions containing a target and background. For best results a representative set of background samples are needed. Further one needs targets appearing on as many different backgrounds as possible.

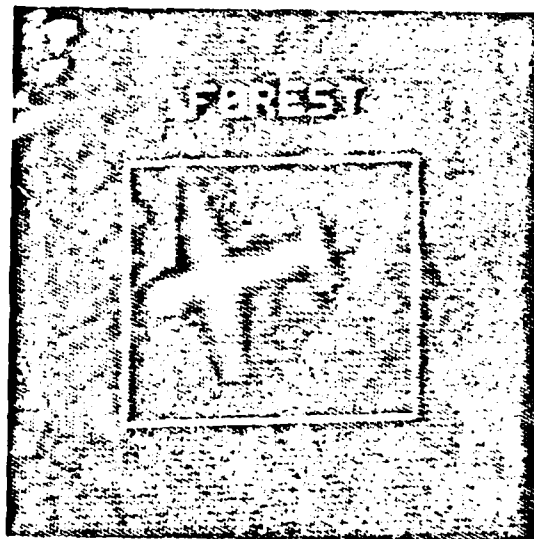
To test these procedures two experiments were performed. The first was based on data from a single channel (.55-.60 micrometer) of a multispectral scanner image and a digitized airplane. The background classes were river, grass, trees, forest, coal yard and developed area. Figure 17 shows the size of region used, the target on a forest background and the forest region without the target. Table 1 shows both the training and testing results. Note only one table is needed since the training and testing results were identical.

The second experiment was based on data taken from a high resolution scene. Only one background class was considered i.e. runway/taxiway. Again the target was a plane. Table 2 gives the training results obtained from experiment.

Both these experiments indicate that texture measures can be used



a



b

Figure 17. Shows a sample of the regions used in the target recognition study. (a) Shows a region representing a forested background. (b) Shows a plane superimposed on this background.

VERIFIED CLASSIFICATION	COMPUTER CLASSIFICATION			ACCURACY
	TARGET	BACKGROUND	TOTAL	
	TARGET	205	2	207
	BACKGROUND	2	204	206
	TOTAL	207	206	413
OVERALL CLASSIFICATION ACCURACY				99.0 %

MEASUREMENTS SELECTED FROM 84 MEASUREMENTS:

- | | |
|--------------------------------|---------------------------------|
| 1. Local Homogeneity (1, 102°) | 7. Local Homogeneity (10, 102°) |
| 2. Entropy (14, 18°) | 8. Entropy (5, 18°) |
| 3. Entropy (1, 18°) | 9. Inertia (10, 102°) |
| 4. Inertia (6, 18°) | 10. Local Homogeneity (5, 18°) |
| 5. Entropy (2, 18°) | 11. Local Homogeneity (14, 18°) |
| 6. Entropy (12, 102°) | |

Table 1. The training results obtained when river, grass, trees, forest, coal yard and developed area. Note the 10% jackknife testing results were identical to the training results.

VERIFIED CLASSIFICATION	COMPUTER CLASSIFICATION			ACCURACY	
	TARGET	BACKGROUND	TOTAL		
	TARGET	35	0	35	100%
	BACKGROUND	0	40	40	100%
	TOTAL	35	40	75	100%
OVERALL CLASSIFICATION ACCURACY					

Measurements Selected:

- | | |
|--------------------------------|---------------------|
| 1. Energy (1,60°) | 4. Inertia (2,160°) |
| 2. Inertia (5,60°) | 5. Energy (1,150°) |
| 3. Cluster Prominence (2,150°) | |

Table 2. Training results obtained using real data. The background class was runway/taxiway. Data was taken from the high resolution urban scene used in the segmentation study.

to detect target. Further the procedures used are very similar to the ones used in the segmentation procedure. This uses a unified type favor to the scene analysis techniques which are evolving.

The results of the target recognition research is reported in [33].

7. A THEORY OF TEXTURE MEASUREMENT DEFINITION

Historically, measures used in image analysis have either been defined heuristically [1,2,3,5,7,8,34] or defined by assuming some mathematical model for the scene and then estimating the parameters which define this model [35,36]. Unfortunately, both methods have yielded unsatisfactory results. Note, measures defined in Equations 1-5 do not gauge all the important texture context information in the cooccurrence matrices. This implies the need for another method for defining measures. In this section a formal method for defining texture measures will be outlined.

Currently the software required to employ the process is being written. Further an initial set of perceptual ranking experiments have been completed. It is hoped that within a few months new measures can be defined using the process.

The framework for this texture measurement definition process is based on the concepts of a perceptual transform, a perceptual space, a measurement transform, a measurement space, and a similarity transform. Let W be the set of all possible textures and let W denote an element of W , i.e., $W \in W$.

Definition 3: The perceptual transform, $\Pi(W) = [\pi_1(W), \pi_2(W), \dots, \pi_n(W)]^t$, is the vector of visual features "computed" by the human perceptual system. Two textures W_1 and W_2 are visually distinct iff $\Pi(W_1) \neq \Pi(W_2)$.

Definition 4: The perceptual space, Ω , is an n -dimensional vector space where each axis corresponds to a visual feature "computed" by the human perceptual system, i.e., each axis corresponds to a component of

the perceptual transform $\Pi(W)$.

The perceptual space, Ω , and the perceptual transform are related by $\Pi: W \rightarrow \Omega$. The perceptual transform and perceptual space play an important role in all image analysis measurement definition problems since the ultimate objective of any algorithm is to at least match human perceptual abilities.

Definition 5: The measurement transform, $M(W) = [m_1(W), m_2(W), \dots, m_k(W)]^t$, represents the vector of texture measures computed from a texture where each component $m_i(W)$ is a texture measure.

Definition 6: The measurement space, M , is a k -dimensional vector space where each axis of M is a component of $M(W)$. Clearly, $M: W \rightarrow M$.

Given the desire to "match" human perceptual abilities the goal of the measurement definition problem can be defined in terms of a similarity transform.

Definition 7: A similarity transform, Σ , is a correspondence which maps the points of Ω into the points of M , i.e., $\Sigma: \Omega \rightarrow M$.

Definition 8: The set of measurements defined by $M(W)$ is said to match human perceptual ability if $\Sigma(\Pi(W)) = M(W)$ for all $W \in W$.

The definition establishes the goal of a measurement definition problem, namely, given Σ define the measurements M such that

$$\Sigma(\Pi(W)) = M(W). \quad (10)$$

Theoretically the "best" set of measures are those which satisfy Equation 10 when Σ is the identity matrix. Unfortunately given the present state of perceptual psychology and neurophysiology such an objective is impossible to obtain. About all that can realistically be considered is a broad class of possible Σ . The objective is to abstract a set of

requirements which define this class in such a manner that any transform in this class will force a "high degree" of similarity to exist between Ω and M .

One such set of requirements on Σ is as follows:

1. Σ should be one-one;
2. if \underline{V}_1 and \underline{V}_2 are two vectors in Ω then $||\Sigma(\underline{V}_1) - \Sigma(\underline{V}_2)|| = ||\underline{V}_1 - \underline{V}_2||_p$ where $||.||$ is some norm on M and $||.||_p$ is a perceptual norm on Ω .

Note that requirement 1 guarantees that for any two visually distinct textures, W_1 and W_2 , $M(W_1) \neq M(W_2)$, a most desirable trait. Further requirement 2 assures that perceptual similarity will be preserved with textures being close together in Ω being also close together in M , a trait desirable for image segmentation.

The last desirable trait for a measurement set is one that is hard to phase in terms of Σ . It expresses the desire for as few measurements in the measurement vector as possible.

3. For each measure m_i a component of M , there exist two visually distinct textures, say W_1 and W_2 , such that $m_i(W_1) \neq m_i(W_2)$ but $m_j(W_1) = m_j(W_2)$ for all $j \neq i$.

Using these requirements one can define a formal measurement definition procedure. What is required to use this procedure is that one specify the type of intermediate matrix from which the measures are to be defined and the general form one will allow the measures to take. For the purposes here these specifications are given in the form of two underlying assumptions of the process.

Assumption 1: The cooccurrence matrices contain all the important texture-context information.

Assumption 2. The information concerning the visual qualities of texture patterns that is contained in the cooccurrence matrices can be gauged using measures which are linear with respect to the elements of these matrices. That is only measures of the form

$$m = \sum_i \sum_j a_{ij} s(i,j,\delta)$$

need be used, where m is the measurement the a_{ij} are constants and $s(k,j,\delta)$ is an element of the cooccurrence matrix $S(\delta)$.

While assumption 2 might seem very restrictive, one would suspect that the visual information contained in a cooccurrence matrix is related to the size and dispersion of the elements of the matrix. Classically the dispersion of elements or mass over some bounded region has been measured using moments. Noncentral moments represent only one form of possible linear function computed from the matrix $S(\delta)$.

Recall that requirement 2 specifies that the measures preserve textural similarity, i.e., that given any two textures W_1 and W_2 , $||M(W_1) - M(W_2)|| = ||\Pi(W_1) - \Pi(W_2)||_p$ where $||.||$ is a norm on M and $||.||_p$ is a perceptual norm on Ω . To verify this design objective one must have a perceptual norm. The norm which seems best suited for the measurement definition problem is called "the law of comparative judgment" developed by Thurstone [37]. Using this norm, the experimental data used would consist of a number of texture pairs. This ranking would be obtained by considering n textures and forming every possible pairwise combination of them. Using these pairs as data, two pairs would be shown to the observer at a time. The observer would be asked to pick which of the two pairs is the most visually distinct. Given the responses an overall ranking of the relative discriminability can be obtained. Let r_i be the relative ranking

of texture pair i . Further let $R = [r_1, \dots, r_s]^t$, $s = \binom{n}{2}$ be the vector of all the rankings.

Suppose W_{1i} and W_{2i} are the two textures which comprise texture pair i . Given a measurement set $M(W)$ the question is, does

$$||M(W_{1i}) - M(W_{2i})|| = r_i \quad (11)$$

where r_i is the ranking obtained from the law of comparative judgment. Clearly, it seems unlikely that a measurement set can be defined such that Equation 11 is exactly satisfied for $i = 1, \dots, s$. Rather it seems more probable that for each possible measurement set $M(W)$

$$||M(W_{1i}) - M(W_{2i})|| = r_i + e_i$$

where e_i represents an error term. Consequently, the more reasonable thing to do would be to pick the measurement set which minimizes the sum of the squares of the error terms, i.e., a least square fit.

The above strongly suggest that a least squares procedure could be used to define measures which would optimally satisfy requirement 2. To use a least square method to define the measurements, i.e., the constants a_{ij} , one must know the number of parameters for which one is solving. The number of parameters translates into the number of measurements for which one wants to solve. Unfortunately, initially the number of measurements that is needed is unknown to us. The procedure is to first solve for only one measurement, then two, then three, etc. Obviously as the degrees of freedom increases the residuals will get smaller. Consequently, one cannot just look at the sum of squares of the error terms to determine the number of measures actually needed. Rather the procedure must be that after one solves for K measures, one verifies whether or not $K + 1$ measures are needed. This verification is similar to verifying requirements 1 and 3. This

verification can be done using linear programming methods and a modified form of the Gagalowicz texture synthesis procedure [38]. Incidentally, it is design objective 1 which demands that one verify that $K + L$ measures are needed before one solves for this many measures.

The above measurement definition process is clearly one which is completely driven by the available data, i.e., the set of texture pairs considered. As such the data represents a knowledge base upon which the algorithm arrives at the measurement definitions.

Further, in creating the texture pairs to be used it is important to keep in mind the purpose of the study. The desire is to create a set of measurements which can watch the capabilities of spontaneous human texture perception. It is desired that the measurements "resemble" the primitive mechanisms of human perception. This point is important because it seems highly unlikely that a simple "norm" on the measurement space regardless of the set of measures used will ever be able to completely match the human judgment of similarity. Consequently, in selecting the data, it seems appropriate not to use real world textures. Judgments about familiar textures could be clouded by learned cognitive reactions rather than based solely on the values of "primitive features" extracted by the visual system. Hence we are using randomly generated patterns synthesized using, for example, the a Markov generation procedure [4].

This research would seem to indicate that a formal method for defining texture measures is possible. If it is, much of the guesswork can be taken out of the measurement definition process and hence better, more robust measures would result. Admittedly the procedures presented are based on a number of simplifying assumptions. However, the validity of the assumptions can be checked by examining the quality of the measures which

result. This quality can be tested by using a classification result comparison on a number of real world problems.

Interested readers are referred to [39].

8. SUMMARY

During the course of this research project a number of fundamental image analysis problems have been studied. These studies have been directed toward improving our understanding of texture analysis and image segmentation. Texture algorithms were studied because texture patterns must be discriminated in a wide variety of scenes. We also have long believed that texture algorithms have a wider applicability than traditionally thought and could form the bases for a general image segmentation algorithm.

The first part of our research investigated texture analysis algorithms. A mathematical procedure for comparing algorithms was developed. An improved algorithm called the SSA was developed which provided for a statistical and structure analysis of texture patterns. This formulation also showed that cooccurrence matrices in this form of analysis could characterize all known texture patterns where difference could be perceived by humans. Existing measures extracted from the cooccurrence matrices were shown to be deficient. New measures were defined and shown to measure structure such as periodicity of a texture pattern. In order to more systematically study the measurement definition problem a theory for defining texture measures was developed. This theory forms a basis for defining measures which characterize perceptual features used by humans. This theory should allow us to substantially improve the SSA texture analysis system by defining improved measures.

The image segmentation problem was also considered. An image segmentation strategy appropriate for texture analysis was devised. A

number of statistical procedures were devised for handling regions in the segmentation process. Basically, these procedures allow one to determine if the region is recognized, unrecognized or is a boundary region. The system was tested on a high resolution urban scene. Good results were obtained and many of the theoretical results predicted for the texture operators were found in the data. The problem of locating isolated objects on targets was also studied. The procedures developed for image segmentation were applied to this problem and yielded good results.

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APPENDIX A

LIST OF PUBLICATIONS

RESULTING FROM RESEARCH

SPONSORED BY THE

AIR FORCE OFFICE OF

SCIENTIFIC RESEARCH

The following represent a selected list of publications which have resulted from research sponsored by AFOSR.

1. Harlow, C. A. and R. W. Connors, "Image Segmentation," Dahlem Workshop on Biomedical Pattern Recognition, May 1979, Berlin, Germany. (Invited).
2. Connors, R. W. and C. A. Harlow, "A Theoretical Comparison of Texture Algorithms," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. PAMI-2, No. 3, May 1979, pp. 204-222.
3. Harlow, C. A. and R. W. Connors, "The Theoretical Development of Texture Algorithm Based on Statistical Models of Texture," Workshop on Image Modeling, Chicago, Illinois, August 1979. (Invited).
4. Connors, R. W., "Towards a Set of Features Which Measure Visually Perceivable Qualities of Textures," Proceeding of the IEEE Computer Conference on Pattern Recognition and Image Processing, Chicago, Illinois, August 6-8, 1979, pp. 382-390.
5. Harlow, C. A. and R. W. Connors, "Image Segmentation and Texture Analysis," Proceedings of SPIE Conference, San Diego, California, August 1979. (Invited).
6. Harlow, C. A., J. M. Hill and R. W. Connors, "Image Analysis Techniques and Remote Sensing," Proceedings of the Corps of Engineers Remote Sensing Symposium, Washington, D.C., October 1979. (Invited).
7. Connors, R. W. and C. A. Harlow, "Toward a Structural Textural Analyzer Based on Statistical Methods," Computer Graphics and Image Processing, Vol. 12, No. 3, March 1980, pp. 224-256.
8. Harlow, C. A., R. W. Connors, M. Trivedi, "Texture Analysis of Remotely Sensed Data," Tenth Workshop on Applied Imagery Pattern Recognition, September 1981, Washington, D.C..
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11. C. A. Harlow, R. W. Connors, R. E. Vasquez-Espinosa, and D. A. Dirosa, "Textural Analysis Methodologies for the Segmentation Urban Scenes," Proceedings of the IEEE Conference on Pattern Recognition and Image Processing, Dallas, TX, August 1981.

12. Trivedi, M. M., R. W. Conners, C. A. Harlow and R. E. Vasquez-Espinosa, "Segmentation of Urban Scenes Using and Extension of Pairwise Classification Approach," Presented at the International Symposium of the Machine Processing of Remotely Sensed Data, Purdue University, West Lafayette, Indiana, June 1981.
13. Harlow, C. A. R. W. Conners, M. M. Trivedi, D. A. Dirosa, and R. E. Vasquez-Espinosa, "Texture Analysis and Classification of Urban Scenes," Proceedings of IEEE Southeastcon, Huntsville, Alabama, April 5-8, 1981, pp. 115-119.
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15. Conners, R. W. and R. E. Vasquez-Espinosa, "A Theory of Texture Measurement Definition," Proceeding of 6th International Conference on Pattern Recognition, Munich, Germany, October 1982.
16. Trivedi, M. M., C. A. Harlow, R. W. Conners, and S. Goh, "Target Detection in Digitized Imagery Using Texture Operators," Proceedings of the IEEE Region 3 Southeastcon, Orlando Florida, April 1983.
17. Trivedi, M. M., C. A. Harlow, R. W. Conners, and S. Goh, "Characterization and Detection of Targets in Black and White Aerial Images Using Texture Operators," to be submitted to Computer Graphics and Image Processing.

APPENDIX B

LIST OF PERSONNEL SUPPORTED

BY THE

AIR FORCE OFFICE OF SCIENTIFIC

RESEARCH

The following is a list of personnel which have been supported by the grant.

1. Charles A. Harlow, Professor
2. Richard W. Conners, Associate Professor
3. Ramon Vasquez-Espinosa, Graduate Student
4. Don Middleton, Graduate Student
5. Semon Goh, Graduate Student
6. Don Dirosa, Research Associate

APPENDIX C

LIST OF INTERACTIONS

WITH OTHER DEFENSE DEPARTMENT FACILITIES

In an effort to apply the knowledge gained from AFOSR sponsored research to various Air Force missions the investigators are interacting with a number of Air Force installations. For example, a six month study was conducted under an RADC subcontract to segment a high resolution urban scene. The techniques employed were a result of the investigations sponsored by AFOSR. The results of the study were reported in a special section at the IEEE Conference on Pattern Recognition and Image Processing held in Dallas, Texas in 1981. Also a paper which describes these results will appear in Computer Graphics and Image Processing.

More recently the investigators have been interacting with personnel at Eglin Air Force Base. The point of interest here is using image analysis methods in target recognition experiments. Currently, the investigators have formulated an approach to this problem which is again based on results obtained from AFOSR sponsored research. The results of this target recognition research has been reported at a number of conferences and currently a journal article is being prepared for submitting to Computer Graphics and Image Processing.

In order to further relate our work to Defense Department needs a number of other laboratories have been visited. These include Corps of Engineers Waterways Experiment Station, and the Engineering Topographic Laboratories. For reference the following list of contacts is provided.

- 1.) Don Bush
RADC/IRRE
Building 240

- 2.) Jerry Becker
Defense Mapping Agency Aerospace Center/STT
St. Louis Air Force Station, Missouri, 63118
- 3.) Lt. Colonel Ankeney AD/DLMI
Eglin AFB
Florida, 32542
- 4.) Dan Cress
Victor Lagarde
Corps of Engineers
Waterways Experiment Station
Vicksburg, Mississippi 39180
- 5.) Melvin Crowell, Jr.
Director Research Institute
Engineering Topographic Laboratories
Fort Belvoir, VA 22060
- 6.) Robert Brown
Principal Scientist
Pattern Analysis Laboratory
Naval Ocean Research and Development Activity
NSTL Station, Mississippi

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